Reputation in peer-based learning environments

Thieme Hennis
Delft University of Technology, the Netherlands
Stephan Lukosch
Delft University of Technology, the Netherlands
Wim Veen
Delft University of Technology, the Netherlands

ABSTRACT

This paper proposes a reputation model to support peer-based learning in online communities. Based on literature on learning and trust and reputation, we developed a reputation framework to analyze reputation systems. Based on lessons learned from a number of successful online reputation systems, we developed a reputation model to support knowledge sharing and management, quality assurance, and increase user engagement in peer-based online learning communities. The description of the model includes a conceptual and mathematical representation, a process description to support implementation, and an evaluation framework. A simple example shows how the model can be applied.

INTRODUCTION

The Internet is a platform that offers new possibilities to learn and build knowledge with others. The decentralized aspect of the network allows anyone with an Internet connection to participate in this process, but this poses new challenges to the way we judge about information, provide learning support, and evaluate learning results. Massive online learning requires new mechanisms through which support, guidance and evaluation can take place to optimize learning effects for participants involved. Considering learning environments that provide access to all, new socio-technical systems are needed in order to bring these new learning environments to maturity. A critical issue in getting there is how to create sustainable learning processes where participants can rely on each other and available content. Trust is an underlying concept for individuals to learn from and with each other in an online community. Implementing systems fostering trust through reputation can enhance the learning effectiveness, and provide alternatives for the traditional pedagogical approaches still in place in current e-learning courses. Formal education could profit from such new learning environments adopting these pedagogical approaches and related technical systems.

Forums, online communities, and professional networks are these new learning environments, where people find and share information, collaborate and learn on demand. A significant challenge is to motivate people to participate in the knowledge-sharing and learning process. Especially in peer-based learning environments, where learning depends on the effort of all participants, it is essential to provide enough incentives to participate and share information with others. This chapter will focus on how data analysis and reputation technologies can improve engagement and learning in online communities.

In this chapter, we describe the need for an online reputation system for peer-based learning environments, present a model with design requirements, and propose an evaluation framework to evaluate a prototype in a community.

Organization of the chapter

This chapter contains a background section, a core section, and a concluding section. Below, we describe the content per section.

- The background section is divided into two parts. First, it elaborates on changes in the learning landscape, with a focus on self-organized and peer-based learning systems. In this context we focus on two things: (i) trust in recommended peers and information and (ii) motivation to contribute and help each other online. The second part of the background section describes the relevance of reputation management in order to improve trust amongst peers as well as motivate them to participate, contribute, and help each other.
- The core section starts with a framework to evaluate online reputation systems. The model is used to evaluate a number of successful online trust and reputation systems, including Google PageRank, eBay, StackOverflow, and impact factor. We draw lessons from a variety of reputation systems, and use these lessons to develop a reputation model. The model can be used to develop reputation systems in peer-based learning environments. In addition, we propose a process description for the development of the reputation model in an organizational context, and an evaluation framework to evaluate and improve the reputation system.
- The concluding section focuses on relevant research directions, such as Cross-community Reputation.

BACKGROUND

In 2008, George Siemens and Stephen Downes organized an online course on Connectivism and Connective Knowledge (CCK08). Over 2200 persons worldwide actively participated in an online, peer-based learning network. Because the organizers were unable to assess and give individual feedback to each of the students, called the teacher-bandwidth problem, they motivated students to give peer-feedback, using technologies of all kind: virtual worlds, blogging, commenting, RSS feed-readers, Moodle CMS, and much more (Downes, 2008a). The course was a so-called Massive Open Online Course, given for free, as part of a research project by the two organizers (Mackness, Mak, & Williams, 2010).

Open education has grown from sharing repositories containing courseware, to a variety of online initiatives, including full-fledged online e-learning courses, open source learning environments, and self-organized online courses. All these initiatives have the objective of providing better access to learning through the provision of free learning resources on the Internet (Brown & Adler, 2008).

The course by Siemens and Downes, together with several other similar initiatives the last couple of years, adds a new element to the open education spectrum: guidance and peer-support. Connectivist and networked learning approaches focus on the ability of the network as a whole to learn, and to learn from the network. Connectivism describes a form of knowledge and a pedagogy based on the idea that knowledge is distributed across a network of connections and that learning consists of the ability to construct and traverse those networks. It implies a pedagogy that seeks to describe 'successful' networks (as identified by their properties diversity, autonomy, openness, and connectivity). Also, it seeks to describe the practices that lead to such networks, both in the individual and in society (Downes, 2008a; Siemens, 2005).

CCK08 shows how open education is evolving from the provision of static courseware, to interactive and dynamic learning networks. But, even though it gave access to learning resources, and provided guidance, it offered official accreditation to only a very limited group: only 25 (less than 2 percent of the students) could be evaluated. Traditional methods for evaluation and assessment seem inadequate for an online context. Rather than focusing on automating learning tasks, and providing automatic feedback through intelligent systems, a more feasible and sustainable approach to overcome the "teacher-bandwidth" problem seems to be self-organization (Wiley & Edwards, 2002). Hence, the challenge for future online learning is to focus on creating sustainable self-organizing online learning networks, in particular how to develop mechanisms by which learners engage in connecting, sharing and collaborating. We will propose a strategy how to achieve such learning networks based on the concepts of trust and reputation. We think that the approach we describe in this paper may also apply for knowledge-based organizations aiming at facilitating networked learning for their employees, customers and business-to-business relationships.

Learning on the Web

The Internet and the numerous online communities of practice and professional networks provide opportunities for informal, self-regulated and networked learning. Above all, the Internet offers relatively cheap access for individual learners worldwide to connect with people and find relevant content. The Internet is an environment in which skills can be developed that are needed in a technology driven, and rapidly changing society (Brown & Adler, 2008). The skills that learners develop in regular education systems are different from those developed in peer-based communities (Soekijad, Huis in ’t Veld, & Enserink, 2004; G Stahl, 2003; Etienne Wenger, 2000).

The social nature of learning

A popular psychological theory is constructivism, which argues that humans construct knowledge and meaning from their experiences (Bruner, 1991; Piaget & Cook, 1952; Vygotsky & Cole, 1978). Constructivist educational theory focuses on concept development and deep understanding, rather than behaviors or skills, as the goals of instruction (Amory & Seagram, n d). Personal development and deep understanding happens through the construction of meaning by the learner himself, not through transmission from one person (the teacher) to another (the learner). The fundamental principle of constructivism is that learners actively construct knowledge through interactions with their environment (Hout-Wolters, Simons, & Volet, 2000). Therefore learners are viewed as constructing their own knowledge of the world.

“*For effective learning, knowledge should be uniquely constructed by people through play, exploration and social discourse with others. Learning objectives presented in constructivist learning environments should be firmly embedded in context, and should, at least in some way, represent every day life situations. Learners should also accept responsibility for their own learning and be self-motivated to explore different knowledge domains.”* (Amory & Seagram, n d)

The central point of social-constructivism is an individual's making meaning of knowledge within a social context (Vygotsky & Cole, 1978). Learning as a social practice is well established and dialogue is one of the corner stones of social constructivism. This makes online communities such potentially effective places for learning. The interactions in online communities is being maintained through a sense of community and social capital through information flow, altruism, reciprocity, collective action, identities, and solidarity to support the development of democracy (Ackerman et al., 2004; Bouman et al., 2007; Kollock, 1999; McLure-Wasko & Faraj, 2005). These are central elements that need attention in an online social learning context.

Widely adopted learning theories behaviorism, cognitivism, and constructivism, and combinations of them, do not sufficiently explain the effect of technology in our lives and learning activities. George Siemens and Stephen Downes have attempted to explain learning in a digital age by combining and enhancing different learning views, and developed Connectivism (Downes; Siemens, 2005; 2006). An important distinction from social constructivism is the emphasis on learning that happens outside a person’s mind (i.e., teaching your computer to think for you). Siemens argues that in the Information Age the learning process concerns activities such as synthesizing and recognizing patterns, meaning making, and forming connections between specialized communities. Know-how and know-what is supplemented with *know-where* as the understanding of where to find the knowledge needed. Connectivism addresses learning outside the person, knowledge stored in databases or other electronic information holders accessible through the Internet. It describes a form of knowledge and a pedagogy based on the idea that knowledge is distributed across a network of connections and that learning consists of the ability to construct and traverse those networks. This implies a pedagogy that seeks to describe 'successful' networks, as identified by their properties, such as diversity, autonomy, openness, and connectivity; and seeks to describe the practices that lead to such networks, both in the individual and in society (Downes). Connectivism extends the notion of learning as a personal, internal change (Illeris, 2003) to a network change: Non-human elements act as actors in the network and the medium itself is part of wider networks. Learning is not only focused on oneself, but on one's network: what are the tools and elements in my network that support searching for and synthesizing knowledge? A smart learner is able to design a personal network of learning instruments and people, giving him an advantage over other learners who rely only on internalized knowledge.

Learning in online communities

The term 'situated learning' locates learning in the process of co-participation and in the field of social interaction, not in the head of individuals to get an inter-subjective understanding and meaning of something (Lave & E. Wenger, 1991). In communities, learning means moving from the peripheral (lurking, being introduced into processes, people, etc) into the center (sharing expertise, making decisions). Peripheral participants do not accumulate knowledge and skills but are introduced in processes, routines, networks, relevant issues, and approaches within the community.

"The individual learner is not gaining a discrete body of abstract knowledge which (s)he will then transport and reapply in later contexts. (...) There is no necessary implication that a learner acquires mental representations that remain fixed thereafter, not that the 'lesson' taught consists itself in a set of abstract representations." (Allert, 2004)

Learning as knowledge creation is seen as the epistemological foundation of CSCL, Computer Supported Collaborative Learning. Paavola, Lipponen and Hakkarainen explain learning as a process of inquiry, especially to the processes where something new is created and initial knowledge is either enriched or transformed during the process (Paavola, Lipponen, & Hakkarainen, 2004). Hence, learning goes beyond the information given. In a knowledge society, we should focus on collaborative processes of creating knowledge (Allert, 2004). This type of learning comprises of open, ill-structured problem solving processes, focuses on communication and collaboration. Stahl refers to learning as shared meaning making, which is not understood as a psychological process which takes place in individuals' minds but as an *"essentially social activity that is conducted jointly - collaboratively -- by a community, rather than by individuals who happen to be co-located"*. Meaning is not transferred from one thinker to another, but is constructed (G Stahl, 2003).

New developments in the science of learning also emphasize the importance of helping people take control of their own learning. Since understanding is viewed as important, people must learn to recognize when they understand and when they need more information. Effective learning environment therefore focus on sense-making, self-assessment, and reflection on what worked and what needs improving (Paris & Winograd, 2003; Siemens, 2005; G Stahl, 2003; Gerry Stahl, Koschmann, & Suthers, 1999).

Recommender and reputation systems in education

Historically, education has focused more on memory than understanding. An emphasis on understanding leads to one of the primary characteristics of current theories of learning: its focus on the processes of knowing (Piaget & Cook, 1952; Vygotsky & Cole, 1978). Humans are viewed as goal-directed agents who actively seek information. They enter a learning process with a range of prior knowledge, skills, beliefs, and concepts that significantly influence what they notice about the environment and how they organize and interpret it (Lave, 1988; Lave & E. Wenger, 1991). This, clearly, can have both positive and negative consequences for the learning process and their abilities to remember, reason, solve problems, and acquire new knowledge. Effective learning environments, effective support systems for learning, and effective teachers therefore take into account the background of a learner. The effectiveness in learning environments can therefore be enhanced when there is substantive information about the learners and the information (McCalla, 2004). Recommender systems and standards have been be developed that take into account the background, needs, and level of a learner, and see if there are matching characteristics with information or other learners. More advanced technologies have been proposed that automatically generate metadata based on interest and interactions in online learning environments (Lemire, Downes, & Paquet, 2008; Vuorikari, Manouselis, & E Duval, 2006; Wolpers, Najjar, Verbert, & Erik Duval, 2007).

Online communities and networks provide a potentially effective place for learners to engage in meaningful interactions with peers and experts. A learner's past is relevant and influences the learning experience. Therefore, recommender systems often focus on the allocation of human and information resources more effectively (and automatically) based on a learner's past and information about usage of a learning object.

This chapter will provide a framework to define and use typical online community actions and interactions that relate an evaluation or assessment of a human or information resource. Suppose that someone or something is evaluated as a positive or valuable resource. If information can be captured that describe the context in which a positive evaluation of the resource takes place, then this information can be used to recommend the resource in other situations. The recommendation shows the resource's ability to solve a problem or contain expertise or certain skills that are requested for. In formal education, the equivalent are diplomas or grades for human resources or and reading list, readers or book titles for information resources. In formal education, this is hierarchically organized. We want to know how this can be organized in a peer-fashion. We assume the following:

A primary motivation to learn in formal education relates to ensuring an economic position or job suiting your ambitions and capabilities. People trust formal education helping them achieving their long-term and short-term goals. Informal online learning networks are still lacking trust as learners do not get standardized diplomas with civil effect. However, informal online learning networks relying on an online reputation system may well convey similar trust levels amongst participants and employers as formal diplomas do. In that case, people will consider online learning as a viable alternative to formal learning. Within online reputation systems, individuals can accumulate a reputation profile depending on any activities helping the learning network or community as a whole by means of peer-based learning and tutoring. People will trust each other based on their merits, which are usually linked to a specific domain of knowledge. The aggregate reputation of the community as a whole gives insight in the quality of a community and its constituent members. This will foster a sustainable and lifelong peer-based online learning system, offering alternatives for current learning practices and courses. Such systems might well serve life long learning activities of masses as they do rely on their participants rather than on a teacher with limited reach.

As defined in this assumption, both trust (in the reputation system) and motivation (of individuals to maintain and sustain the learning system) are key and intrinsically linked aspects. In a peer-based learning environment, peers are collaboratively responsible for feedback, analysis, and support. So the question we should ask then is: What actions and interactions that relate with professional reputation should be mined and analyzed in order to make this person contribute (what actions sustain the community)? How can he or she benefit from a contribution, and have the feeling that invested time in the community and its people will not be for nothing (trusted reputation)? As learning emerges from interactions between and contributions by people in a community, we must focus first on motivation. Reputation systems guide behavior, so how can we connect desired behavior, personal motivation, and peer-based learning? The objective of a reputation system in peer-based learning environments is the improvement of its viability, defined as the continuous ability to provide an online environment in which learners can make meaningful interactions and learn from each other.

In the next part, we focus on reputation and trust issues in education in more detail.

Trust and reputation

Above, we concluded with challenges for peer-based learning in online communities. The Internet provides numerous opportunities for active, self-regulated and networked learning. It is a giant network of networks in which people communicate. The architecture and intuitive tools that have been built allow for creation and sharing of information in social and professional networks. The

Internet has been used to disseminate educational resources for free, and there have been projects that offer support and guidance, as well as educational technology, for free, in addition to the resources. It seems that scalable and sustainable models are being developed for massive online courses by supporting students to reflect and assess contributions in a peer-based manner. But we have also seen that there is a lack of models and systems that support recognition of learning activities in peer-to-peer communities.

In this section, we look at different approaches to learn lessons for the design of a valid system that supports recognition and improves assessment in online communities. The need for such systems, and for research in this direction, is made clear by Schmidt et al:

"..despite improvements in methodology, assessment practices have a tendency to focus on easily quantifiable measurements rather than contextualized behaviors, dispositions, and attitudes. For our open education accreditation model, we are interested in retaining the goal in accreditation of accurately reflecting learning and skills to enable individuals and firms to negotiate employment arrangements efficiently. However, we also acknowledge that the skills needed in the 21st century are radically different from those tested and accredited in the past. Open education communities have certain unique characteristics that are ideally suited to the development and recognition of such new abilities in its individual members."

"..a better understanding of indicators for knowledge and skills in open education communities is needed. Such indicators would consider processes and describe types of communication and interaction as well as behaviors within a community of learners." (Schmidt, Geith, Håklev, & Thierstein, 2009)

They further argue that digital portfolios, digital trails (what you leave behind on the web), and aggregations of individual opinions and ratings are used to improve relevancy in online learning environments. Reputation models that calculate trust can enhance and improve the accuracy these environment. Kollock has shown that reputation is one of the fundamental motivations of people to share and create knowledge in online communities (Kollock, 1999).

Professional reputation in online communities
Tuomi (2007) describes that the social importance of formal educational certificates is now declining, as the capabilities, interests, and reputations of people can be directly evaluated using information and communication technologies.

"Instead of asking whether a job candidate has a formal educational status, a potential employer can now review the candidate's actual track record, blog postings, and possibly e-portfolios." (Tuomi, 2007)

In some expertise areas, such as computer programming, employment opportunities often depend on a track record that can be reconstructed by search engines and personal blogs. The digital identities of persons now consist of their own representations of achievements and experiences, as well as reputations that accumulate through the comments of others. Formal educational certificates may be components in such digital representations of capabilities, but their relative importance will diminish (Tuomi, 2007). Labalme and Burton (2002) call this reputation capital, and argue that such values can be carried through systems (Labalme & Burton, 2002).

McLure-Wasko and Faraj (2005) isolated individual motivations and social capital considerations as main influencers on knowledge sharing. They had found that people tend to actively contribute to online communities when they perceive that this enhances their professional reputations (McLure-Wasko & Faraj, 2005). In an essay on the future of online learning (2008), Stephen Downes writes the following;

"What will emerge for learning institutions, as for most other services, is a system of reputation management that is integrated into the search process. Recommender systems, as such systems are now called, will employ pattern-matching software to find resource providers for potential clients. The software will draw information from a wide range of other services, including information about the institution that produced the resource. As we have seen, though, with search engine optimization (SEO) and other attempts to mislead reputation systems, there will continue to be a tension between the trust we put in such systems and the degree to which they can be infiltrated or corrupted. Reputation systems based on data that can't be replicated or imitated will acquire the most trust, and these will most likely be based on verifiable identity and interactions within social networks." (Downes, 2008b)

Because reputation and trust are highly interrelated topics, we will define them below, before continuing this chapter.

Defining trust and reputation

Trust is the confidence in or reliance on some quality or attribute of a person or thing, or the truth of a statement. In fact, trust is often used interchangeably with related words like credibility, confidence or reliability (Wang, 2005). Trust is the basis for interpersonal interaction and especially for cooperation in a social network. Merriam-Websters Collegiate Dictionary states that trust is *"..the assured reliance on the character, ability, strength, or truth of someone or something."*[1] Kinateder and Rothermel (2003), from an Artificial Intelligence perspective, define trust in an entity as the belief that under certain circumstances, the entity will perform in a certain way (Kinateder & Rothermel, 2003). Another definition of trust commonly found is the one of Diego Gambetta *"... trust (or, symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action..."* (Gambetta, 2000). Lik Mui (2002) is adapting this definition slightly in emphasizing the importance of expectation instead of working with probability: *"a subjective expectation an agent has about another's future behavior based on the history of their encounters"* (Mui, Mohtashemi, & Halberstadt, 2002).

Reputation is information used to make a value judgment about an object or person (Farmer & Glass, 2010). The scientific research in the area of computational mechanisms for trust and reputation in virtual societies is a recent discipline oriented to increase the reliability and performance of electronic communities (Sabater & Sierra, 2005). Usually, reputation is based on actions or achievements done by individuals or groups. Whereas trust in between agents can be defined as a subjective expectation an agent has about future behavior, reputation has more global characteristics.

Why are reputation systems so important for fostering trust among strangers? Online reputation systems are developed to obtain and maintain measures of trust between people, and intend to offer incentives to behave in a certain way. When people interact with one another over time, the history of past interactions informs them about their abilities and dispositions. The expectation of reciprocity or retaliation in future interactions creates an incentive for good behavior. An expectation that people will consider one another's pasts in future interactions constrains behavior in the present (Paul Resnick, Richard Zeckhauser, Friedman, & Kuwabara, 2000).

Game theoretic approaches to reputation are predominant nowadays, resulting in systems that are likely to give good results in scenarios that concern simple interaction patterns between human beings, such as those in online marketplaces. However, when the complexity of the scenario increases, these models are not so good. They reduce trust and reputation simply to a probability or perceived risk in decision-making (Sabater & Sierra, 2005). This seems to be too restrictive in scenarios where the complexity of the agents in terms of social relations and interaction is high. Reputation cannot be understood as a *"static attribute, rigidly codified as footprints of social hierarchy"* (Squazzoni, 2004). On the contrary, it has dynamic properties, because reputation attribution is a socio-cognitive mechanism that takes root in communication processes. Both the

[1] http://www.merriam-webster.com/netdict/trust

"reputed agent" and the "reputing agent" should be taken into consideration, and the context and relevant processes in which trust is established.

Context, transitivity, and cross-community reputation
An important point regarding trust is the fact that trust is not transitive (Abdul-Rahman & Hailes, 2000). Just because X trusts Y and Y trusts Z, does not necessarily mean that X would trust Z. The problem is usually one of context. So X cannot be sure in which context Y trusts Z. For this, approaches have been suggested to incorporate context or categories into trust systems (Tan & Thoen, 2000). To translate too rigidly or literally from the sociological and psychological domains can be difficult and would lead to high dimensionality. Therefore, a set of categories or contexts would need to be chosen, for which the trust between peers could be transitive for individual categories and could be applied inter-categorically where possible.

Golbeck and Hendler have proposed the reputation inference algorithm, to be used with semantic web based social networks, founded on the Friend-Of-A-Friend (FOAF) vocabulary (Golbeck & Hendler, 2004). The FOAF project defines a mechanism for describing people and who their connections are. They extended that ontology by adding binary trust relations (trusts and distrusts). Golbeck and Hendler focus on social networks, and provide an analysis of trust between people and how this trust could be inferred. In this chapter, we focus on the inference of trust from object to the object's author. Transitivity then means that someone's trust in an object (i.e. a paper) is inferred by the author/creator of that object. Many other trust and reputation systems intend to provide a 'global' characteristic (Golbeck & Hendler, 2004; Josang, 2007; Kamvar, Schlosser, & Garcia-Molina, 2003), but in the importance of context requires a different approach: reputation not as a global but a local characteristic.

A reputation in one online community is usually not reused in another community (Vu, Papaioannou, & Aberer, 2009). For example, a seller on eBay cannot bring use his/her reputation to another online marketplace. The other way around, it is also impossible to 'bring' your reputation to eBay and replace or merge it with your eBay reputation. The trust people have in eBay's reputation system, and in the company, may be affected if it becomes dependent on other systems, managed outside eBay. Yet, there are considerable advantages for communities and individuals to share reputation between communities (Vu, Papaioannou, & Aberer, 2009). Resnick et al. argue that limited distribution of feedback decreases its effectiveness, because reputation (both the good and the bad) relates to only a single online arena (Paul Resnick, Richard Zeckhauser, Friedman, & Kuwabara, 2000). The main advantages of using cross community reputations (CCR) are (i) leverage of reputation data from multiple communities; (ii) producing more accurate recommendations; (iii) reputation accumulation: a user does not have to build a reputation from scratch; (iv) users are able to maintain (global or community-specific) offline reputation certificates; and (v) faster establishment of new virtual communities by importing reputation data from related communities (Gal-Oz, Grinshpoun, Gudes, & Meisels, 2008). Also, the trade of reputations may lead to new opportunities for communities as a reputation provider. For example, a reputation provider for experts in solar energy may offer communities and their members to share reputations across a network of solar energy companies, researchers, and institutes. For this to happen, reputations need to be constructed in a way that allows for interoperability and synchronization between communities. Kinateder & Rothermel propose a directed graph of categories to support mapping of dependencies and relationships in different reputation systems (Kinateder & Rothermel, 2003). Related context increases the likeliness of having similar incentives and ranking between communities, improving compatibility and thus the possibility of reputation mapping. Berlanga et al. warn for privacy issues that will arise when participants' online identity and reputation are transferred from one community to another (Berlanga, Rusman, Bitter-Rijpkema, & Sloep, 2009).

There are two preconditions for cross-community reputation systems: ontology mapping and trust relationships. First, a community should define and follow a reputation ontology. If the most important reputation mechanisms and mappings have been described, elements of different ontologies can be mapped and related. Secondly, there is a trust relationship between communities. Concerning

CCR, trust can be defined as the extent to which one community relies on another community to provide reputation for members of both communities (Gal-Oz, Grinshpoun, Gudes, & Meisels, 2008). As trust depends on context, more contextually similar communities are more likely to be able to share and agree upon ontologies.

In the following sections, we will look at various systems that address trust and reputation. By looking at different reputation systems we hope to learn lesson for the development of a reputation system that can sustain online peer-based learning environments. The analysis of reputation systems consists of three steps. First, we develop an evaluation framework that is based on requirements to sustain peer-based learning in online communities. Then, we choose the reputation systems that are subject to evaluation. Finally, we do the analysis and draw lessons for both the evaluation framework and the reputation system.

DEVELOPING A REPUTATION SYSTEM TO SUSTAIN PEER-BASED LEARNING

As described in the previous section, reputation systems can improve trust and guide behavior (or stimulate desired behavior). We can learn from existing systems to see how they address the trust and motivation issues. This implies three steps:

1. Create an evaluation framework to assess different systems,
2. Choose the reputation systems to assess
3. Evaluate and analyze the chosen reputation systems

Based on the analysis of different reputation systems, we will propose a reputation model, including a conceptual and mathematical representation, scenarios and examples, an implementation process description, and an evaluation framework.

An evaluation framework to evaluate trust and reputation systems

In our evaluation of online reputation systems, we use the ontology on Web reputation systems proposed by Farmer and Glass (Farmer & Glass, 2010). They describe how reputation consists of numerous 'reputation statements'. The following model represents a statement:

Figure 1 - Reputation model (Farmer & Glass, 2010)

The above statement is an elementary particle of every reputation system. Simple reputation systems calculate a reputation based on one type of claim, from a small number of sources, to a small number of targets. For example, on eBay, the source is usually the buyer, the claim consists of 4 elements (price, quality, communication, and delivery), and the target is the seller. The system merely aggregates all the claims by buyers, and shows the (weighted) average. This is called a reputation container, which is a compound reputation statement with multiple claims for the same source and target. Despite being simple, it is a very effective reputation system, and allows people to make better choices when they want to purchase something online.

Google, another reputation system we look at, is much more complex and different from eBay in many respects. Still, we can use the above formalization in the description of ranking websites. From simple statements, one can create a very complex reputation system. A robust reputation system may integrate reputation models coming from different sources. For example, curriculum vitae usually contain both formal (education) and informal (interests, committees) aspects, so HR people can more easily make decisions the persons to invite for an interview.

In the evaluation of reputation systems, we focus on rules and ideas on how to design a generic reputation system to support peer-based learning in forums and online communities. The evaluation framework uses the above grammar to define and describe objectives, workings, and elements of the different reputation systems and addresses specific concepts, issues, and challenges mentioned in the background section. These include:

- Quality: What is the concept of quality in the system? Is the system capable of filtering good from bad?
- Context: How is context embedded in the reputation statements? Is reputation very contextual or generic? How is reputation being reused? Who accepts/trusts the reputation? Is it (re)used in a professional context?
- Sustainability: how does the reputation system influence the sustainability of the environment? How is the system itself sustained? Issues as motivation, dependencies, scalability, and good and bad behavior are treated here.

The above information culminates in a short description of lessons learned per reputation system. The sum of lessons learned will then be presented as a set of design requirements and suggestions. As such, we intend to provide guidelines for the development of reputation systems that can support peer-based learning.

EVALUATION OF REPUTATION SYSTEMS

In the previous chapter we evaluated different trust and reputation systems in order to define requirements for the design and implementation of a reputation system to support and sustain peer-based learning in online communities. In the following, we consider systems with different characteristics to cover all elements of our reputation framework.

GOOGLE PAGERANK

If we define trust as the confidence in something or someone to perform or deliver something, we can look at Google as a system that ensures the probability of a result to deliver the result (answer) on the question (query) asked. Google has proven to be able to deliver highly relevant search results for free, facing a rapidly expanding and more dynamic Web, meanwhile becoming highly profitable.

According to their mission statement, is Google trying to make the world's information available to the people. By measuring interactions, usage, links etc. they are able to recommend relevant information resources and services to people. Combined with targeted ads, they are able to sustain their services.

Google's PageRank system calculates relevance of a web resource by looking at its relation with other web resources. PageRank relies on the uniquely democratic nature of the web and uses its vast link structure as an indicator of an individual page's value (Brin & Page, 1998; Lewandowski & Höchstötter, 2008). In essence, Google interprets a link from page A to page B as a vote, by page A, for page B. Votes are weighed according to the PageRank of the voter. The image below makes clear how this works, in a simplified form: A's link to B is assigned more weight than c's link to B, because of differences in popularity (PageRank). Next to popularity Google analyzes contextual factors of webpages and their relations to allow semantic searching.

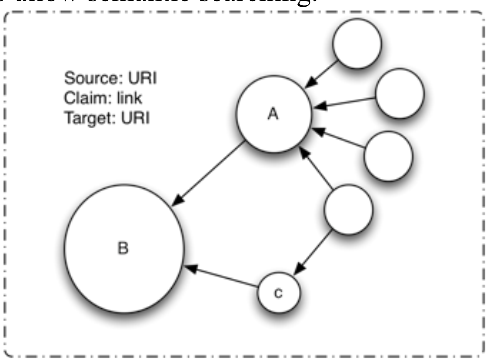

Figure 2 - Google PageRank

In the PageRank algorithm, sources and targets are URI's, or internet 'things'. All things that can be found by typing in a link can be a source as well as a target. The claim is a vote from one link to another. One of the most interesting aspects of PageRank is the characteristic that in the voting process, the reputation of the source counts.

Quality

Quality is derived from measuring static and dynamic relationships between URIs. Based on these relationships and their connection value, Google is able to define a notion of relevance of a webpage and knows how to connect this notion to specific contexts. If a search query corresponds to a context, Google shows the most relevant and highest valued results for that context.

Context

In more than one way, Google determines the context of a URI: first of all, it looks at its content (title, description, texts, etc.). Secondly, it looks at its links (both ingoing and outgoing links). Thirdly, it continually improves knowledge about a URI by looking at usage, clicks, etc. This information is also being used to know more about the Internet user, in order to provide better contextualized advertisements (in addition to search results). Commercial results are shown separately.

Sustainability

Google is sustainable in many respects:

- It does not rely on specialized committees who analyze and evaluate the relevance of a webpage, but uses available data of the Internet's interconnected websites to determine relevance and quality. Obviously, people are needed to maintain and update the software, but the quality assurance process is fully automatic. Therefore, it has been able to scale to the size of the Web.
- Google provides a range of services, making users of those services more dependent on Google. Also, in order to be found on the Internet, you must play according to the rules set by Google. There is an incentive for website owners and content contributors to behave as desired by Google (adding keywords to your website, for example).
- Bad behavior can be detected, and rules are in place to counter that (such as removing from search results).

Conclusions

Google shows that giving away services for free can be highly profitable and sustainable. Especially for individuals participating in peer-based learning environments, this can be relevant: you can profit from sharing your knowledge. With regard to the reputation system, we learn that automated interpretation of available data about behavior and connections is possible and scalable. When we look at a single target object (a URI), we see that votes for that URI are weighed according to the reputation of the source URI.

EBAY SELLER REPUTATION

eBay is the largest online retailer. Without its reputation system, it would probably be not as successful. Trust is essential in commercial transactions, and the reputation system is designed such that individual buyers can easily assess whether or not a seller is trustworthy. An experiment by Resnick et al. (2006) examines the value of eBay's reputation system (P. Resnick, R. Zeckhauser, Swanson, & Lockwood, 2006). It was found that only 0.6% of all the ratings provided by buyers and only 1.6% of all the ratings provided by sellers were negative, which seems too low to reflect reality. The possible explanation they provided for the positive rating bias was that positive ratings are a sort of exchange of courtesies, whereas negative ratings are avoided because of fear of retaliation from the other party. The eBay reputation must increase trust in trustworthy sellers and filter out untrustworthy sellers. The high number of daily transactions shows that the system itself is good enough to filter out the worst people.

On eBay, sources are buyers and sellers are targets. The claims are structured in four categories: "Item as described", "Communication", "Shipping time", and "Handling charges". Buyers give a 5-star rating for each of the categories after purchasing. The evaluation is linked to a specific purchase.

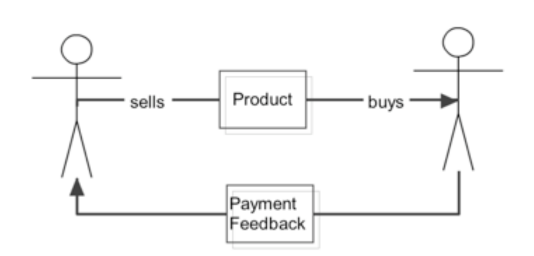

Figure 3 - eBay reputation

Quality

eBay is very clear about quality (or trust): a seller must not ask an unreasonable price, must ship fast, must not add unreasonable extra costs, and must reply on emails fast. Sellers who are not trusted are checked and removed from the system. In addition to the explicit ratings, there are implicit parameters, such as "Number of transactions" and "Years active". Also, the whole transaction history is publicly shown. As such, eBay approaches trust and reputation from different angles.

Context

The eBay system is a rather simple system. Its assumption is that if a person is trustworthy for 9 consecutive transactions, he/she will also be trustworthy the 10^{th}, regardless of the type of transactions and what is being sold.

Sustainability

The eBay reputation system is essential for eBay. The way sellers are rated trustworthy happens in a very decentralized way, and on the basis of transactions. Even though human resources are needed to maintain and improve the system, and settle cases, it seems like the business generated by the system outweighs the resources needed to maintain it. The desired behavior is clear, see above. Sellers who behave as such are more likely to be trusted and will be able to sell more. The eBay trust system has proven to be scalable, hosting millions of transactions per day. The sellers on eBay are not able to transfer their reputations to another marketplace, which is understandable from the perspective of eBay, but not less preferred from the perspective of sellers, who need to stick to eBay in order to improve their reputation.

Conclusions

eBay is very clear about desired behavior (setting price/quality, communication, handling charges, etc.). This explicitly guides sellers' behavior, and also motivates them to conduct as many transactions as possible. As shown by Resnick et al., direct feedback can be ambiguous (P. Resnick, R. Zeckhauser, Swanson, & Lockwood, 2006). eBay solves this with the inclusion of more implicit ways to represent trust and reputation are used, such as years active, and number of transactions.

GURU PROFESSIONAL REPUTATION

Malone & Laubacher (1998) coined the term 'e-lance economy', meaning an economy largely based on temporary organizations of individuals that emerge and dissolve when business opportunities arise and disappear, and where IT serves to link individual nodes (Malone & Laubacher, 1998). Online marketplaces, such as Guru.com provide a place for individuals and organizations to find each other and employ or be employed. The mechanism is similar to eBay but concerns the ability of people to do a specific task. Reputation consists of implicit parameters (including amount of money earned), and direct feedback by employers. Freelancers can also provide a resume, portfolio of work, and do standardized tests to prove certain basic skills. Another way to increase reputation is to answer questions on the forum. The image below shows how freelancers are presented in Guru, showing the most important trust parameters, including badges (community accreditation).

Figure 4 - Guru.com reputation

The objective of the reputation system is to match employers and freelancers. An employer is content when he finds the right person to solve his/her problem. A freelancer is happy when he finds the right job for the right price and can work whenever he wants to. For employers, the reputation system has the objective of providing a level of trust in freelancers. For freelancers it is an instrument to show accomplishments, become distinguishable, and increase in value. An employer is the source making a claim (rating and comment) about a freelancer after the freelancer has done a job. As with eBay, people are needed to solve disputes. Payment is also a strong indicator of value-transfer, and thus taken as an indicator of a freelancer's value.

Quality

Various indicators define the quality, or value, of a freelancer: accumulated earnings, ratings and recommendations, and other indicators as badges. In addition, a freelancer can add credentials and diplomas to support claims of expertise or skills. The quality of a freelancer is equal to the perceived quality of his work for others. As with eBay, this is a very direct way of rating.

Context

Expertise or skills are (by definition) limited, which makes a personal reputation always contextualized to an expertise domain. It is likely that a freelancer does jobs within a single arena, and a reputation is therefore valuable within that same arena. Guru defines those arenas, so software companies can find programmers and a movie director can find a scriptwriter.

A reputation on Guru relates to activity generated on Guru, but it is not unthinkable that a freelancer uses his Guru reputation in another professional context.

Sustainability

Even though the system depends on some employees to settle cases, it is almost entirely self-organizing. Guru is comparable with eBay. Sellers on eBay depend on their reputation as freelancers on theirs on Guru. Contrary to eBay, the context in which reputation is earned does matter: you don't want to hire a financial consultant to solve an IT issue. Guru freelancers are motivated to do a good job. Employers are motivated to support freelancers and pay in time.

Conclusions

Reputation is approached from different angles. In addition to employer feedback and rating, history of transactions and a portfolio is visible which makes it more difficult to 'game' the system.
A reputation ontology guides the feedback of employers about work delivered by the freelancer (i.e. price, quality, communication, etc.). Similarly, freelancers rate employers (i.e. ability to pay in time).
Employers and freelancers find each other within a static, explicit context: the industry expertise area. Designers are rated on the quality of their designs, not anything else. Finally, internal and external accreditation possibilities improve trust in the system.

IMPACT FACTOR & ACADEMIC REPUTATION

The impact factor is one of the most important reputation systems in science. It is criticized, but still widely used and regarded as one of the most important quality measurement and assessment systems in the scientific community (Saha, Saint, & Christakis, 2003). The impact factor is a measure reflecting the average number of citations to articles published in science and social science journals over a certain period. It is frequently used as a proxy for the relative importance of a journal within its field, with journals with higher impact factors deemed to be more important than those with lower ones. The objective of the system is to provide insight into the quality of research and journals. It does so by accrediting journals with a high impact factor. Resource allocation and financial systems have emerged that use the information to allocation funds. As such, it is a very powerful system because it is embedded in a larger ecosystem. The impact factor is shown in relation with other elements in the simplified figure below.

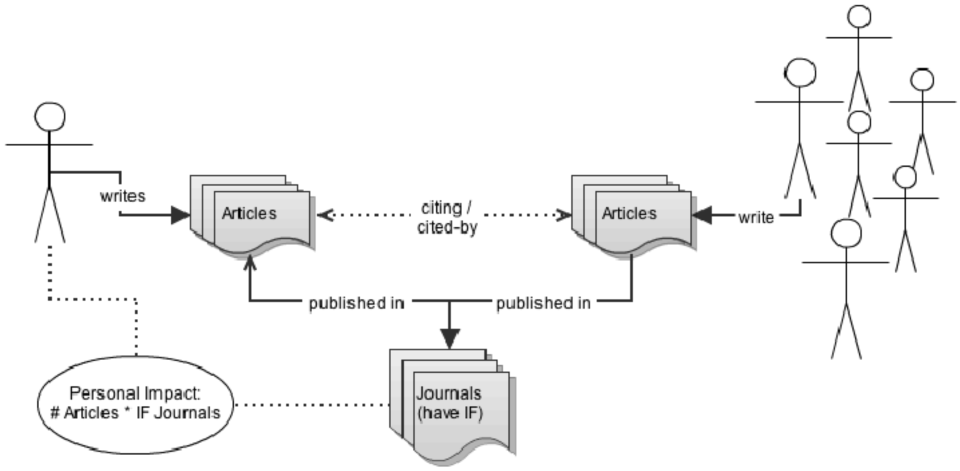

Figure 5 - Academic publishing

Universities use the impact factor to assess the quality of research of its departments, and allocate funds based on that assessment. Hence, the influence of the impact factor should not be underestimated. The impact factor received a lot of criticism because of its focus on the journal in which a paper is published, rather than the number of citations it receives (Bollen, Rodriguez, & Van de Sompel, 2006; Bordons, Fernández, & Gómez, 2002; F. Hecht, B. Hecht, & Sandberg, 1998). In reaction, several other initiatives have emerged, including the h-index, and PLoS (Public Library of Science) Article Level Metrics, focusing more on individual impact and citation level. Currently, debates online focus on how this information can be improved with a social impact level, by measuring popularity and usage (Montenegro-Montero, 2009).

Sources in the system are academic articles. A journal is an aggregate target and the calculation is based on the average number of claims (citations) it receives. Calculation often happens within specific domains, such as Medicine.

Quality

According to the system, the amount of citations a journal receives relative to its number of publications is the essence of scientific quality (impact). Obviously, the total number of citations is also relevant. The system includes measures to counter self-citation and fraud.

Context

The context of an article is usually made clear with keywords, and the conference of journal where it is published usually shows the domain of it. The impact factor also considers different domains in determining the impact factors.

Sustainability

The strength of the system is its adoption by universities, governments and research institutes, who pay for research through the allocation of money and resources. The allocation is based partially on publications in highly ranked journals. The acceptance of the Impact factor system is high. The reputation and prestige of a university is directly correlated with its ability to publish in highly ranked journal. Therefore, they motivate their employees to write for journals with a high Impact factor in their field. These journals want to keep a high status and Impact factor, so they will only accept really groundbreaking and well-written articles.

Self-citation is mentioned as a way to game the system, and to increase the impact factor of a paper. This however, is not always the case (Gami, Montori, & Wilczynski, 2004). Reputation systems that do not address these issues are less valid and therefore less trusted. Approaching quality from different angles, and being open for human intervention and control can counter bad behavior and fraud.

Conclusions

The impact factors is a reputation system that is widely used to allocate financial resources. It influences the behavior of institutes at large, and individual researchers in specific. In a complex, automated system as the impact factor, it seems that the exact calculation algorithms of reputation are not entirely known. This could possibly prevent fraudulent behavior.

A one-dimensional representation of quality that takes into account only one claim-type is likely to be criticized. More dimensions and a larger scope take into account different claim types, such as popularity and PageRank. The social web and larger variety of methods to publish research materials is an opportunity and a threat for the impact factor. An opportunity because more information and more sources of information are available to calculate real impact, but a threat because the system may not be able to cope with this variety, leading to a loss of trustworthiness. Publishing research happens increasingly online and the consumption of academic research increases in complexity as well (from read-only to link, rate, recommend, save for later, write about, review, etc.). Likewise, the evaluation, and *claim*-process rises in complexity as well. This complexity should be addressed by the reputation system that aims to give insight in the quality of research.

A final interesting issue is the fact that the impact factor of a journal influences the value (even in financial terms) of individual papers. This is similar to PageRank that also assigns extra weight to links (votes) that come from popular websites. Even though there are different approaches, we see that sources in a reputation statement can carry a weight.

STACKOVERFLOW QUESTION & ANSWERING COMMUNITY

StackOverflow is an online community for people discussing IT-related issues. There are now numerous websites using the original StackOverflow reputation system, collectively named the StackExchange. On the forum community members can ask questions and/or provide answers and comments. The answers receive votes by community, and the answer with the highest amount of votes is chosen as the best answer. In addition to votes and answers, members can add tags to questions and answers. These tags play an important role in the reputation of users. Part of member profiles is dynamically updated with the tags of Q&A topics they participate in, as shown in the picture below.

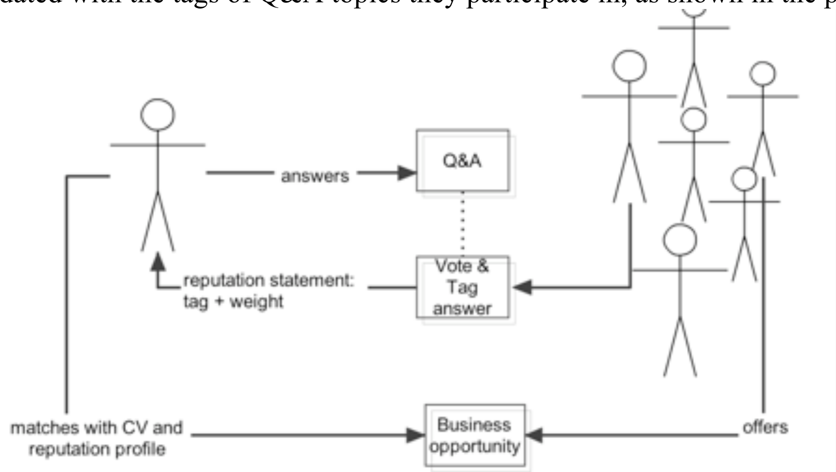

Figure 6 - StackOverflow

StackOverflow wants to keep the quality of questions and answers high. On the forum, people are the *sources*, who vote (*claim*) and tag (contextualize) *targets* such as answers, questions, and comments.

Quality

Quality is measured in terms of votes for answers, questions, and comments. Answers are assessed on quality and are contextualized using tags. This makes it easy for Search engines as Google to use the content on the community and for people to find the content they need. “Good” behavior, or in other words: giving the right answers, earns points, expertise tags, and badges. Each person has a personal profiles showing their reputation and history of questions and answers on the site.

Context

StackOverflow is a very interesting example from the perspective of context. Because every question is contextualized with keywords, an individual contributor develops a list with keywords representing the topics of the questions in which they have shown their expertise. These keywords each have an individual score, depending on the votes for the answer (or question). It therefore becomes a very contextualized profile. The community itself maintains the list of keywords (a domain ontology).

Sustainability

Members of StackExchange sites are very serious about their reputations. The reputation they earn can be shown on employments sites. The reputation system also motivates members to specify tags for a question, to formulate questions well, and to provide high quality answers. Additionally, it motivates them to scrutinize answers on their quality. The community maintains the keywords. There is no danger of excessive use of tags, because it is useless from the perspective of members to have a reputation on a keyword that no one uses. As such, the reputation is specific and uses a commonly agreed and maintained ontology defining the topics and domains.

Conclusions

StackOverflow shows how in the modeling of reputation, context and quality are combined through the involvement of the community. At the same time, the community is motivated to maintain and agree upon topical keywords representing the knowledge and subjects dealt with by the community. Unlike more static representations of context (i.e. eBay: “communication”, “price”, “delivery time”, etc.), StackOverflow is able to combine the contextual factors (tags assigned to questions) with votes to make a dynamic representation of the quality of a person based on his/her contributions. It is self-organized contextualization. There is no imposing of taxonomy or structure for all questions and answers.

Another relevant conclusion is that, if a member wants it, reputation can be shown to 3rd parties. These potential employers can search the database and get software experts from the community. Their Q&A reputation is important, and forms an important incentive for the members to answer questions (and show-off/share expertise). Sharing expertise for free can lead to employment and improve professional reputation. Active and self-directed learning is possible and sustained in decentralized communities, if the right tools and mechanisms are in place. Reputation, which is crucial for the electronic freelancer, depends on contributions. It is an important incentive to collaborate in order to get business opportunities.

CONCLUSIONS ON THE REPUTATION SYSTEMS

In the previous sections, we have analyzed a variety of reputation systems. The lessons learned can be used to develop a reputation model for peer-based learning environments. As we explained in the background section, there is a need for this. A reputation model can be used to develop a community specific reputation system that is able to sustain the exchange and reuse of useful information and accrediting the contributors of the information. It can also stimulate learners to consult peers or be consulted by peers who have a question or request. Below we summarize the outcomes of the various reputation systems and describe implications for the design of a reputation system for peer-based learning environments.

General remarks

The objectives and nature of the analyzed reputation systems have similarities and differences. Most of the described systems are rather simple, and focus only on the core interactions and most significant processes. All systems have the objective of recommending people or information, to provide information about how an object or person can be trusted. eBay shows the information and allows an individual to make his or her own choice. This is possible because the information it gathers can be represented fairly easily. Google, on the other hand, accumulates so much information about websites that it would be impossible for any human being to interpret, so their interpretation algorithms do that. Individuals only get a list of recommended websites for their search query. Thus, it is important to describe the nature (complexity) and objectives of the community, the relevance of reputation, and the objectives of the reputation system.

How should a peer-based learning community be described?
A peer-based community can be any forum or professional network where people exchange information and learn from each other. The context is problem-based and active learning. There is no pressure on anyone to engage in the learning or teaching processes, and motivation must come from interest, need, or visibility/reputation.

Reputation of a target object is represented by a set of keywords and each of these keywords has a reputation value. The value is based on the claims made about the object by other objects (source objects) and the authority of the source objects to make these claims. The design of a reputation system for peer-based learning environments starts with the description of core knowledge-sharing processes and typical contributions of a community or organization. The description contains processes and contributions that could benefit from a reputation system, the claims that relate to a type of quality, and the source objects that make these claims. These processes could be interrelated and form a complex network of targets. In a human-based community, the objective is to motivate people to produce high-quality target objects. The reputation of *a person* depends on quality of his/her produced target objects.

Quality

The different reputation systems show a variety of sources, claims and targets. In other words, we have seen various implicit and explicit ways to express quality and assign value to persons and objects, including linking, voting, rating, citing, etc. The representation of quality depends on the objective of the system. If the system is a search engine, then quality relates to the position on the results list. If there is a community of people, reputation usually is shown more explicitly, as an identification of a person or object (“Best Answer”, or “99% Positive feedback”).

In the analysis we saw that in the aggregation of information about quality or trust, the systems address both implicit and explicit *claims*. Implicit claims are retrieved by means of logging and interpreting behavior in the system, such as number of links and page-visits (Google PageRank) or number of citations (impact factor). Explicit rating requires the input of users, and could therefore be more subjective as well as contain more qualitative information than an implicit statement. For both implicit and explicit rating there are challenges to overcome. Explicit statements require explicit input and therefore depend on the willingness of users to provide that input. The effort of users must be kept at a minimum. When we scan online behavior for the interpretation of quality (implicit statements), the context of the logged behavior is very important. It is a significant challenge to determine the behavior and processes that need to be monitored and the context in which this behavior takes place. In addition, interpretation rules need to be developed and tested to show the meaning of the monitored behavior. Because the approach is more quantitative, results become viable only when sufficient amounts of data about a specific object or person is generated. Therefore, another challenge is to get enough data. Google PageRank is an example of how simple, implicit statements can be used to structure the Web. Google does not provide users with an explicit “website” rating system, because it knows that it will be used strategically. The size of the web makes it impossible to control, but this is usually not the case of communities, where social control could be possible. If the expressiveness of a statement is low, a larger number is needed to be able to extract a generic meaning. Context analysis could also add meaning to a statement.

What does this mean for peer-based learning environments?
First, describe all relevant statements (check with stakeholders) that are implicit and already part of the system. Find out what these statements in fact mean, and see if the number of statements is high enough to make viable conclusions. In addition, find out if people are willing to provide explicit feedback and how this can be organized and embedded into the system.

An overview should be made of all the implicit and explicit statements (claims), and describe how they are interrelated, and how they should be interpreted. If the interpretation is difficult, contextual information must be added in order to make the right interpretation. Reputation statements can be bundled if they have similar meaning, i.e. explicit ones can support implicit statements. These interpretation rules need to be verified with the user community, and calibrated with through use.

Context

The context of information exchange in a knowledge-based system is complex. It is not like eBay, where the context of a transaction is rather static. It is the eBay platform and the static specifications of the rating: time, quality, etc. On StackOverflow, the context of an ‘answer’ (reputable object) is more dynamic: it is the question which is contextualized by keywords. People on the platform add these keywords. The result is that on eBay, your reputation is generic, and can be simply represented by a number (“99% Positive Feedback”). On StackOverflow, your reputation is specified by keywords.

Depending on the platform and the objective of the reputation system, a choice for dynamic contextualization should be made. On eBay, trustworthiness is very generic: the assumption is probably that trustworthiness does not depend on the type of product. On a knowledge-based platform, capturing the field of expertise and relevant domain for each reputation statement (claim) is necessary to add relevancy. The information allows for grouping of people, recommending content, etc. Making context more explicit is a challenging but necessary task.

What does this mean for peer-based learning environments?
The topics dealt with in a community should be made explicit and made part of the reputation system. It is possible that the community itself maintains the ontology, which can be used to contextualize reputation statements. The context of a reputation statement cannot fully be known in advance. On a forum on mathematics, you know in advance that each question will be related with mathematics, but specific context is added in a more dynamic and bottom-up way (for instance through tagging).

Part of the context of a reputation statement is the *reputation* of the source that makes a *claim*. We have seen with Google’s PageRank principle that the source website’s PageRank rating influences the vote (claim) to another website. We propose the same principle here. Comparing reputation profiles of source and target can result in higher or lower weight to the statement. In other words, if someone has a reputation on “Bronchitis”, he/she is able to answer questions about Lung diseases than someone who has a reputation on “Semantic Web”.

In conclusion, we propose to use context, defined in keywords, as an intrinsic part of a reputation statement, such that a reputation of an object consists of keywords with values (see example StackOverflow). In addition, we propose to use the reputation of a source object to influence the weight of claims coming from this object.

Sustainability

Sustainability is the ongoing ability to meet the objectives of an organization, project, or system. The sustainability of a reputation system is highly related with its acceptance and the trust it generates. The sustainability of a system is related to the effort needed from people and whether or not they are willing to make this effort. On different platforms (eBay, Guru), we saw that dispute settlement is needed. Manual, human intervention may be needed to check or maintain the quality of reputation profiles and recommendations, but it may also inhibit the scalability and growth of the system, especially when the resources required for this, are not available. Reputation systems are under continuous scrutiny of the people making use of it. A changing environment may influence the validity of the reputation system. A system should be well equipped to address changes and accommodate those changes in changes in the reputation system. On the other hand, rapid changes in a system may influence the trust people put in the system.

Motivation is a central element in any reputation system. The aggregation of behavioral data, of personal history and transactions, and its publication, influences the behavior of people in the system. We saw that reputation acquired on the web is used professionally and to earn money. Therefore, gaming the reputation system might have benefits. Most systems use information from different sources and angles to validate data. As we saw, human intervention is sometimes needed to detect and signal wrong behavior.

What does this mean for peer-based learning environments?
The sustainability of a learning system is its ability to provide high-quality resources and support for each learner. Because we are talking about peer-support, we should evaluate the level of participation and willingness to engage in peer-support processes, and the quality and availability of learning resources.

The objective should be to automate as much as possible, so a system relies less on explicit human intervention. This puts the focus on capturing implicit statements. When explicit intervention or support by humans is needed, it should be clear why they would be willing to do this. With the StackOverflow example, we saw that the community is willing to maintain the topic ontology, because their reputations would become *more useful* with a standardized grammar.

The way knowledge and skills are represented, should be understandable and searchable for ‘reputation consumers’, such as peers and potential future employers. Obviously, they relate with core-processes of the community. Check if and how good behavior can be reinforced and put effort in embedding a wider (professional or societal) context into the reputation system.

Something that should be central in the design and development of any system should be: Is it really worth it? How do benefits of the reputation system compare with the costs? An estimation must be made how the system will be maintained and improved. Benefits are described in terms of increased participation, engagement, higher quality & availability learning resources, interest by 3rd parties. Costs are described in terms of financial and human resources, and expertise to maintain the system, rate and evaluate information, adaptation to changes in the environment.

When a system is implemented, it should be evaluated on its merits and costs (above), and on its quality: Does the system produce accepted reputation profiles that express knowledge, expertise, or value? Can the calculated reputation be relied on? Do they relate with the core community processes of peer-based learning and knowledge-exchange? Does it really motivate people to engage in these processes?

Finally, in what way will the system be able to adapt to changes and/or wrong assumptions? How will it implement necessary changes in the rule system and use feedback? Can the system be gamed?

Conceptual and mathematical representation of a reputation system to support peer-based learning

In the conclusions, we find a large number of relevant issues and factors related with reputation systems in peer-based learning environments. Below, we conceptualize the conclusions in a graphical and mathematical representation, and use simple examples with each step. The conceptualization combines the reputation model by Farmer & Glass (Farmer & Glass, 2010) with the conclusions from the previous chapter.

Description of the model

The following model is based on the literature on reputation and examples reviewed in the previous section. We use the simple definition of a reputation statement, proposed by Farmer and Glass (2010):

- A target $T = \{t_1,\ldots,t_n\}$
- A claim $C = \{c_1,\ldots,t_m\}$
- A source $S = \{s_1,\ldots,s_r\}$

We will use these definitions in our proposed reputation model. We propose a model that specifies reputation per keyword, rather than provides a generic measure of trust.

First of all, we define a target and a source. They are both 'objects' (1): objects have a reputation consisting of keyword-value combinations (2). This means that the reputation of an object (which can be a person) is defined by keywords and that each of the keywords has a value.

(1) $$O = T \cup S$$
(2) $$R_o = (k, kv_o) \mid k \in K \wedge kv_o \in R_0^t \wedge o \in O \wedge K = k_1, \ldots, k_t$$

In the scenario below, a and b are target objects, and all except a is a source object. The arrows are claims.

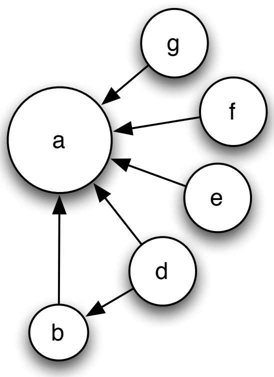

Figure 7 - Example of sources, claims, and targets

We now introduce the concept of a *meta-object*. A meta-object is the creator of target objects. For example, in a scientific community the people are *meta-objects* (not directly part of any reputation statement), and their contributions (papers, articles, etc.) are the objects. In human communities, these meta-objects are people. A person's reputation is an aggregation of the reputation of his/her contributions (all the target-objects produced by this person).

(3) $$MO \subseteq O$$

Obviously, these meta-objects can also be normal source or target objects. We have seen that direct rating can be ambiguous. (P. Resnick, R. Zeckhauser, Swanson, & Lockwood, 2006) Despite that, direct rating is a normal practice in communities, so we must not prohibit that.

To summarize, we look at reputation of *target*-objects. These objects are creates or produced by *meta-objects.* The *meta-object* inherits the reputation of its produced target objects. We then explained that these meta-objects could be source and target objects as well.

```
Algorithm   R_MO
  Forall    o ∈ MO
   Forall   (k, kv_o) ∈ R_o
     If     k ∋ R_MO
            R_MO = R_MO ∪ k, kv_o
     Else
            kv_MO = kv_MO + kv_o
     endif
   endfor
  endfor
```

The example below shows how meta-object MO has contributed a and b. It means that every claim made about a and b will be *inferred* by MO.

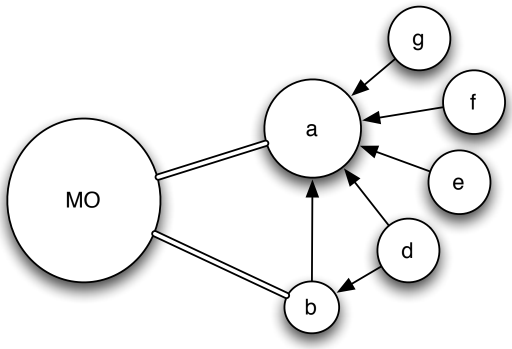

Figure 8 - Meta-object and its contributed objects

When we take the above example, we see that T is the creator of target objects *a* and *b*. All reputation statements directed at *a* and *b* will become part of the reputation of T.

What is a reputation statement?
The reputation of an object is determined by the reputation statements directed at it. A reputation statement is defined in terms of a claim, a source, and a target. We specify this picture by adding context.

- k: affiliate keywords describe the context of a target object. The affiliate keywords can be "passed on" to the object to become part of its reputation. They are discovered or added by people, but <u>not</u> yet part of the reputation. Something can only become part of the reputation through a claim. Affiliate keywords are those keywords in a community that represent the topics and knowledge domains.
- $rv^k_{avg.}$: each keyword has an average reputation value, which is the total reputation value for that keyword of all target-objects (not the meta-objects: that would be double-counting) divided by the number of target-objects.

(4) $$rv^k_{avg.} = \frac{\sum_{i=0}^{n} kv_{o_i}}{n}$$

- w^k_t : Affiliate keyword weight is the weight of a single affiliate keyword in relation to the other affiliate keywords of a target object o. Sometimes, the weights are equally divided, if both affiliate keywords have similar importance in representing the target. If one keyword describes the target better than the other, this can be shown by the affiliate keyword weight.

- w_t: Target weight depends on the type and location of the target, or maybe even the popularity. For example, in a community, an answer to a question can be considered more important than posting a comment, even though both are considered targets that should be monitored. This difference in importance is reflected by the target weight.
- w_c: Claim weight addresses the differences in claims. Some claims, such as official endorsements, may carry more weight than others (like a page visit).
- v_c: Claim value is the actual rating itself, which can be positive or negative.
- w_s^k: Source weight is another word for "authority of a source object to make a claim about an affiliate keyword". Hence, it is the source object's reputation value, specified per affiliate keyword. If the source object has a value higher than the average value, the claim will be reinforced by the source weight. A lower than average reputation score for an affiliate keyword will weaken the claim for that keyword. Source weight can be calculation in many ways, it includes at least some comparison between the source reputation value for a keyword and the average reputation value for that keyword. We add one in order to make claims valid even if the source does not have reputation for that keyword. We propose to calculate the source weight as follows:

(5)
$$w_s^k = \frac{rv_s^k + 1}{rv_{avg.}^k}$$

In order to calculate reputation per keyword, we must split each reputation statement into individual claims containing one of the affiliate keywords. This is important, because sources have reputations consisting of keywords with values. The actual source object weight for an affiliate keyword is calculated by comparing its reputation score for the affiliate keyword with the average score for that keyword.

So, how does a reputation statement look like then? For each of the affiliate keywords, the reputation value for the target is calculated as the product of (i) Affiliate keyword weight, (ii) Target weight, (iii) Claim weight, (iv) Claim value, and (v) Source weight (authority).

(6)
$$c_t^k = w_t^k w_t w_c v_c w_s^k$$

An example is shown in the picture below. The first step in a reputation statement is to determine the affiliate keywords. These can be added manually by the source object, or are already available. Then, for each of the affiliate keywords, a claim is made. In the example, we see that there are only two affiliate keywords, and that the source only has reputation on one of them (Skin diseases). The source weight is calculated for each of the keywords, and as can be seen, the statement (3 stars) weighs 3 times as much for the keyword "Skin diseases" than for the keyword "Sexually Transmitted Diseases".

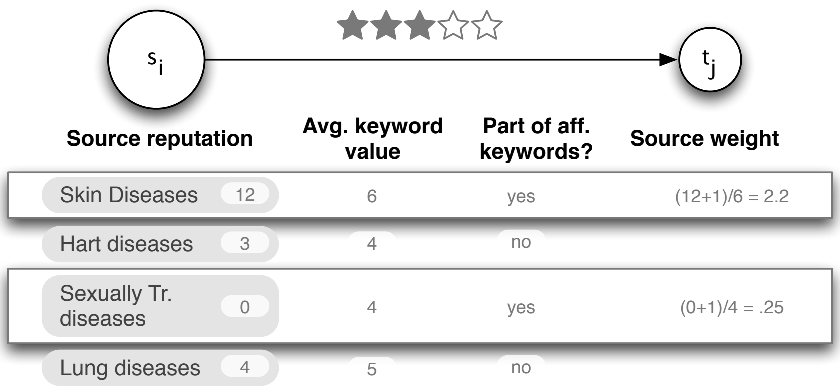

Figure 9 - Reputation statement & calculation of authority

This example makes clear that the source object's reputation influences the weight of a claim *per affiliate keyword*. If a target has 100 affiliate keywords, a reputation statement will be divided into 100 separate claims and for each of the claims, a unique source weight will be calculated.

How are the other weights calculated?
The weights regarding target-types and claim-types are really community concerns. Each community has its own values and norms about what is desired behavior, which should be reflected by the weights assigned to specific targets and claims.

- With regard to *target weights*, we can think of this example: a reputation system of a research institution that supports Open Access establishes lower weights for articles that are published in journals that are not open access. The higher target weight for articles (target objects) that are published in Open Access journals motivates the research institution's researchers to publish there.
- With regard to *claim type weights*, we follow the above example: the institution finds Google PageRank of a Journal more relevant than the impact factor. Google's PageRank (claim type & value) impacts the relative value of a journal (in this scenario *a target object*) more than the claim-type and value of the impact factor. The weight for PageRank is therefore higher than for for "impact factor".

These weights are either defined in advance (in agreement with the community), or the result of a calculation (with parameters defined by the community).

We have already discussed the affiliate keyword weight and authority. In the section about further research, we mention the retrieval and management of affiliate keywords as a very relevant and challenging issue.

Design and implementation process

In order to make a design and develop a viable reputation system, one must be able to define the most important processes and values of a community or organization. This exercise of getting to know and describing knowledge-exchange, management, and quality maintenance is partially normative (influencing behavior), but for the greater part just observing how people share and evaluate information (watching behavior). The following steps will guide the process of defining the reputation system for a particular knowledge-based community.

Step I – Define the target objects, source objects and the claims
The model shows that reputation statements consist of a target, source and claim. In order to make a model, one should understand and model all *relevant* targets, sources, and claims in a system, community, or organization. Relevant targets, sources, and claims are those that are related with core knowledge management and learning processes in the organization or community. The focus should be on processes and objects that are reusable and digital.

- Create overview of knowledge exchange processes and contributions in the community.
  - KM processes. How do people manage/share/create knowledge?
  - Learning processes. How do people learn with and from each other?
- Set boundaries: motivation & technology
  - Motivation. Which processes and contributions would be enhanced by a reputation system?
  - Technology. Which of these processes and results of processes can be monitored online?

Example: LiLa
The example we use is the EU project Library of Labs, a existing EU-funded initiative for the mutual exchange of and access to virtual laboratories (simulation environments) and remote experiments (real laboratories which are remotely controlled via the internet). The portal includes technology like scheduling systems, library resources, and social tools such as a forum and peer-reviewed assessments. At the moment of writing, the portal is not fully functional, so the example is partially imaginative.

On LiLa, the main objective of a reputation system is to support and motivate students and teachers to support each other and answer questions, when they are asked about a specific theory or experiment. As defined above, we define the relevant source and target objects, and all claims.

- Source objects are users: registered and non-registered users.
- Target objects are answers on the forum and assessment reviews.
- Claims are different for the target objects: answers and reviews are not evaluated by the same claims. The table below shows the different claims per target object.

Claim type	Description	Target(s)
Favorite	People can add a review to their Favorites for future reference.	Review
Rating	People can rate a review on a three-point scale: Very helpful – Ok – Not helpful	Review Answer
Clicks	The page visits on the forum topic or review page. This claim type influences the reputation of the target as a whole.	Review Answer

Most knowledge systems are more complex than this, and the list will likely be more extensive.

Step II – Establishing rules for the weights

Secondly, the weights must be defined (or the rules to calculate them). Each claim directed at a target will be divided into separate claims containing for each of the target's affiliate keywords. This means that each of the separate claims is a value-keyword combination. As defined in formula (6), the actual claim for an affiliate keyword is the product of (i) affiliate keyword weight, (ii) target weight, (iii) claim weight, (iv) claim value, (v) source weight. The rules and or static values of these weights must be discussed, discovered, and determined.

Example: LiLa

On LiLa, the weights and values are determined as follows. First, there are affiliate keywords that relate with the location of the target object.

Assessment reviews are placed inside an experiment page. Experiments are explicitly contextualized with keywords (they are part of the metadata set), and each assessment belongs to one experiment. Hence, each assessment review will get the keywords of the experiment it belongs to. On LiLa, keywords affiliated to a target get an equal weight, so if there are two affiliate keywords to a target, each gets a weight of 0,5. If keywords are hierarchically related, the lowest level keywords are the only ones being included, because the target will inherit the higher-level keywords.

There are different target weights for answers and reviews on LiLa, because reviews are considered more important than answers. Similarly, there are different weights for the different claims. The table below shows all the different weights, and the calculation of the reputation value for a reputation statement by user "userID_321" by "userID_426". The keywords affiliated to the target "Review#456" is "carbon-dating" and "radio-metric dating", and the claim is a "Favorite". Below only the part of the claim concerned with affiliate keyword "carbon-dating".

Affiliated keyword	Carbon-dating	Target	Review#456	Claim	Favorite	Source	userID_426
Aff. keyword weight	0,5	Target weight	0,7	Claim weight	2	Weight	3,1
				Claim value	1		

Target object "Review#456" has two affiliate keywords. Each time a source object makes a claim, two reputation statements are issued (one for each keyword), because the source-weight will be different for each keyword. For the keyword "carbon-dating" the claim results in a value of 2.17. It means that the reputation value of target "Review#456", and therefore also its author's reputation value, will increase with 2.17 for that keyword.

Linking the model with the background and analysis sections

The first sections of this chapter focused on learning and education in the 21st century. In this section we connect the reputation model of the previous section with the background and analysis sections on learning, trust, and reputation. First, we argued that learning increasingly happens in open and closed online communities, and that there is a need for quality assurance and insight into people's contributions in these communities by peers as well as potential employers. Recommender and reputation modeling could help in creating trust and motivation, and increase insight in the quality of online contributions. We identified several factors that should be addressed when designing and implementing a reputation system for such communities. These are motivation, quality, context, scalability, and sustainability. Based on lessons learned from existing reputation systems about each of these factors, we developed a reputation model. Below, we describe how our reputation model addresses these factors.

Quality
Quality is a perception, but some people (or objects) are better in perceiving quality than others. The model calculates authority for each keyword and uses this to assign (extra) weight on claims. Someone's reputation is therefore not only communicative, but instrumental in the evaluation process as well.

Context
Context concerns those factors and issues that directly influence the reputation process. Although not extensively, we have proposed numerous ways to include context, most importantly by means of *affiliate keywords*. In addition, we have proposed the inclusion of weights in order to address differences between affiliate keywords, target objects, claim types, and authority. We proposed a model that can be set up rather simply, but can be extended as the complexity of the system requires that.

Sustainability
Sustainability is defined as the ongoing ability to meet the objectives of a system, organization, or project. In our process description, we describe how from the analysis of core-processes and community objectives, we define what could be part of the reputation system. A well-designed reputation system is able to motivate people, increase trust, and gives insight into the quality of a community as a whole or a single entity in specific. Motivation is concerned with the individuals and their willingness to participate as well as the intention of the system to motivate certain (preferential) behavior. The various weights we introduced allow for configuration of the model to support or counter certain behavior. Scalability was defined as the ability of a system to grow when needed or to handle growing amounts of interactions. In our analysis, we relate this with the level of dependence on people to maintain a system. A central element of the reputation model is its emphasis on the utilization of logs and available information about processes and interactions, not on asking people to do something extra.

Evaluation framework

Evaluation must be part of the design of a system from the beginning. It is impossible to design a perfect system. Feedback and analysis is the basis for each new design phase. We suggest addressing the following topics in the evaluation of the system:

Objectives of the organization/system/community
- What are the core processes and contributions needed to sustain the community?
- Who are the most important stakeholders and roles in sustaining these processes or contributions?

Increased motivation/engagement
- Motivation to contribute and be engaged to do the defined core processes
- Involvement of important stakeholders (time online, # contributions, etc.)

Quality of reputation profiles

- Alignment with historical data: Does the information in a reputation profile represent the actual value added to a community (in terms of skills and knowledge), perceived through the eyes of 'target user' as well as other users in the community? In other words: Do people recognize their or other reputation profiles? Do they make sense?
- Alignment with core processes: Is the information contained in a reputation profile related with the defined core-processes and contributions?
- Reusability and contextualization: Is the data on reputation stored in such a way that it can be reused and represented in a human and machine-readable way?
- Gaming: Is it possible to deceive or game the system?

Learning benefits

- Quality of information. Does the average usefulness of information increase?
- Availability of information. Does the production of information increase?
- Willingness of people. Are people more willing to answer a posted question, connect with other people, and support others (see core processes & contributions)?

Professional benefits

- Trust & Acceptance. Is there increased interest or involvement by (the rest of the) organization and third parties?
- Knowledge management. Does the system improve the ability to find professionals or information *just-in-time*?

Financial costs of the development and maintenance of the reputation system

- Initial costs
    - Analysis of the existing organizational structures and processes concerned with knowledge sharing (within the boundaries of the prospected system).
    - Describing design requirements and functional design of the reputation system based on the analysis.
    - Evaluation of the design requirements amongst stakeholders, and development of the actual technical system and algorithms.
    - Implementation and support.
- Ongoing costs
    - Development and implementation of changes in the technical system (based on feedback or changes in the environment).
    - Communication about the benefits of the system and promoting it to various stakeholders.
    - Costs for dispute settlement, updating the reputation ontology, algorithms, etc.

For the development of a reputation system, it is wise to start small, test, and improve in various sequential phases. In addition to retrieving information about the usefulness, quality or failure of a system, this also engages a core group of people to make use of the system. This group of people may be very useful in a further stage. Communicating the potential and long-term benefits of the system to stakeholders is also very important. They decide about the social, financial and technical support for the system and must therefore know about its potential (i.e. motivation of employees, self-organization, peer-based learning, etc.).

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The chapter started with a description of how learning can be organized in a peer-based learning environment. In online communities, people create and share and manage knowledge in a peer-based fashion. We described a need for reputation systems in order to maintain quality and motivate people to engage in peer-based learning activities. Based on literature we defined a number of factors that are relevant in developing a reputation system to support peer-based learning and knowledge management in online communities. Using these factors, we analyzed several successful reputation systems. This analysis resulted in lessons learned for the development of a reputation model we proposed in the previous section. In addition to the model, we describe steps that can be taken in order to use the model and create an actual reputation system for a peer-based learning environment.

The reputation model is a generic model that can be made community-specific. Through observation and interviewing community members, processes, weights, and objects can be defined that represent the reputation and knowledge management processes. This process of designing, implementing, calibrating, and improving a reputation system based on the model brings up many interesting research topics. The model itself provides a good way to structure and research these questions. We define a number of relevant topics below.

Affiliate keywords

The first topic we find highly relevant and important is the challenge of retrieving and managing affiliate keywords. There are various ways to add affiliate keywords to a target, depending on the technology available and the characteristics of the community. Affiliate keywords can be part of a topic-ontology, developed and maintained by the community. Appropriate domains of study include semantic web research (with standards and technologies to define concepts and relationships), latent semantic analysis, information retrieval, and knowledge management. Interesting topics are the discovery or retrieval of affiliate keywords, and the semantics of keywords and relationships. Questions include

- What are effective ways to retrieve affiliate keywords, both through automation and manual input?
- How does reputation flow between connected keywords?
- What is the influence of a reputation system on the level of keywords (as we proposed) on the emergence and or usage of a common ontology?
- How must skills and knowledge be represented? How can semantic web standards be used to develop ontologies?

Claims

Claims form an interesting topic as well, because it focuses on the *meaning of behavior*. Interesting questions include:

- What does it mean when a paper is cited?
- How can skills and knowledge be ‘proven’ in online communities?
- How can personal background, culture, and character traits influence the reputation or rating process?
- What is the influence of negative ratings in the reputation process?

Target and source objects

With regard to target and source objects, we think of the following questions:

- What are common contributions and knowledge-exchange processes in online learning communities?
- What factors influence authority?
- How can authority be understood and accepted outside the community where it has grown?
- What are typical sources, claims, and targets in an online community or forum?

Other relevant topics

Below, we put a number of other relevant questions:

- What is the influence of time on the value of online content?
- How does reputation influence the learning process in higher education?
- How does the introduction of a reputation system within an organization influence behavior?
- What are important factors that indicate the usefulness of such a reputation system, such as group size, number of interactions, topics, and heterogeneity?
- Can the reputation modeling map conversations and topics in real-time?
- What is the influence of online reputation on organizational structures?

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